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Factor Investing in Practice:
Performance and Risk Exposure of U.S. Factor ETFs

Bachelor’s Thesis
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Abstract of bachelor's thesis

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Abstract

I examine U.S. factor ETFs' performance relative to the academic factor portfolios' and evaluate their risk exposures with several asset pricing models. I find that ETFs investing in size, value, momentum, and low volatility strategies offer exposure to the intended factors but the market factor remains as the main driver of their returns. Factor ETFs' performance seems to follow that of long-only rather than long-short factor portfolios, and due to the high market exposure, they have significant co-movement with each other. Despite these drawbacks, factor ETFs have offered higher returns and Sharpe ratios than their respective long-short counterparts, which gives support for the long-only approach to factor investing.

Keywords Asset pricing, ETF, Factor investing, Risk factor, Smart beta

Contents

1. Introduction

Factor investing refers to investment strategies that provide exposure to established risk factors and aim to capture their associated return premiums (Ang, 2014). It is particularly popular through exchange traded funds (ETFs) and nowadays there are hundreds of factor ETFs[1] following size, value, momentum and many other factor strategies. These products are often advertised to investors by referring to academic studies on factors that highlight abnormal returns, diversification possibilities and other benefits (see e.g. factor investing websites of Blackrock[2] and Invesco[3]), but there are major concerns for factor investing in practice. Real-life factor portfolios such as factor ETFs face limitations on shorting, effect of transaction costs, and many other issues that are not present in their academic counterparts. These differences raise an important question: Do factor ETFs work as intended and can factor investing be beneficial also in practice?

Surprisingly little research exists on factor investing although it has experienced significant growth in popularity during the 21st century. Academic literature has proposed hundreds of factors explaining stock returns in the past decades, but it is still unclear how most of these strategies perform in the real world. Considering the current "zoo of factors" and the many false positives (see e.g. Ang, 2014; Harvey et al., 2015) it would be important to evaluate factors also from the perspective of real-life implementability. The few studies conducted on factor investing have also highlighted conflicting results: some researchers claim that factors cannot be captured effectively in real-life portfolios (see e.g. Malkiel, 2014; Jacobs & Levy, 2014), whereas others argue that factor investing is possible and beneficial also in practice (see e.g. Ang, 2014; Blitz et al., 2014). In addition, no one has yet compared real-life factor portfolios' performance directly to the academic factor portfolios', which would highlight their potential differences. Considering the increasingly popularity of these strategies, investors ought to know how these products really work and how significant are the differences between factor ETFs and their academic counterparts.

In this paper I evaluate the performance and risk exposure of a sample of U.S. factor ETFs investing in size (small and large cap), value (value and growth), momentum and low volatility strategies. Using data of ETFs and academic factors from June 2000 to June 2018, I construct portfolios of ETFs following similar investment strategies and compare them to both long-only and long-short factor portfolios. For example, value ETFs are compared to the long-only value factor portfolio and the long-short HML portfolio used in financial research. My analysis consists of three parts. First, I compare the performance of factor ETFs and factor portfolios using both raw and risk-adjusted performance measures. Then I evaluate factor ETFs' potential diversification benefits and show how their co-movement differs from that of factor portfolios. Finally, I perform several regression analyses with different asset pricing models to test whether size, value, momentum and low volatility ETFs can achieve the intended factor exposures and whether there are any unintended factors driving

[1] Throughout this paper I refer to all ETFs providing exposure to long or short sides of academic factor portfolios as factor ETFs. In practice these products are often referred to as smart or strategic beta ETFs.
[2] https://www.blackrock.com/investing/investment-ideas/what-is-factor-investing
[3] https://www.invesco.com/portal/site/us/investors/etfs/strategies/factor-investing/

their performance. My study highlights the benefits of and concerns for factor ETFs and contributes to literature on factor investing and risk factors in general.

The three main results of the paper are as follows. First, factor ETFs' performance seems to follow that of long-only factor portfolios' and they offer higher returns than the long-short portfolios. Also, their risk-adjusted performance matches that of long-short portfolios and small cap, value, and low volatility ETFs have fared better than standard market ETFs during the sample period. Second, I find that the diversification benefits of factor ETFs are modest, but better than what the long-only factor portfolios imply. Third, from the CAPM and Fama-French-Carhart regression analyses I find that factor ETFs offer the intended factor exposures rather consistently but the market exposure remains dominant and some ETFs have also unintended factor tilts. These results are robust to using both value- and equally-weighted portfolios of ETFs and different asset pricing models. Overall my results show that tilting the portfolio towards factors has a notable effect on the performance and risk exposure of factor ETFs, and that factor investing can be beneficial also in practice.

The rest of the paper is organized as follows. Section 2 provides background on factors and factor investing, describes the factor ETF market, and formulates the research questions. Section 3 covers the data of ETFs and factor portfolios and the research methodology. Section 4 presents the results and discusses how they relate to earlier literature and what implications they have for factor investing in practice. Section 5 concludes.

2. Background, motivation, and research questions

This chapter covers literature on factors and factor investing, describes the factor ETF market in U.S. equities, and formulates the research questions.

2.1 Factors and factor investing

Factors are the main drivers of investment performance and risk and have been a hot topic in financial literature for decades. Not surprisingly, more and more factor strategies are also implemented in real-life portfolios such as ETFs and factor investing has experienced significant growth in popularity. This section discusses factors as investment strategies and highlights the major concerns for factor investing.

2.1.1 Relevant factors and their benefits

Financial research has proposed hundreds of factors in all major asset classes throughout the years, but their implementability in real-life portfolios is not straightforward. In fact, there is still disagreement of factors' origin, exact definition, robustness, and significance among researchers, and many proposed factors are deemed as false positives. For example, Harvey et al. (2015) study over 300 factors presented in financial literature with a new multiple testing framework and claim that most of them are likely to be false. To help investors focus on relevant factors, Ang (2014) proposes four criteria. He argues that a factor should: 1) Be justified by academic research, 2) Have exhibited significant premiums (alphas) that are expected to persist in the future, 3) Have return history available for bad times and 4) Be implementable in liquid, traded instruments.

In this study, I focus on size, value, momentum, and low volatility factors, all of which fill the criteria proposed by Ang (2014) and have been widely studied in financial research. Although there are many more relevant factors both in academic literature and real-life factor portfolios, size, value, momentum, and low volatility are among the most established and have the longest return histories to study. To keep the focus of the paper on factor ETFs and factor investing in practice, I will not cover the literature on these factors separately. Instead, Table 1 provides a summary of the factors including the market factor with references to literature. The factor descriptions elaborate on the structure of long-short factor portfolios used in academic research. Finally, Table 1 lists some example ETFs that offer exposure to these factors (long- or short-sides).

Table 1 Factors, literature, and example ETFs.
This table provides a brief description of the factors studied in this paper with references to previous literature and lists some examples ETFs.

Factor	Description	Literature	Example ETFs
Market	Risk premium for investing in equities. Stocks have higher risk than bonds, for example.	Sharpe (1964); Lintner (1965)	Vanguard Total Stock Market ETF Schwab US Broad Market ETF
Size	Small stocks offer greater returns than large stocks in the long run. Portfolio that goes long on small stocks and short on large stocks yields positive alpha.	Banz (1981); Fama & French (1993)	iShares Russell 2000 ETF Vanguard Small-Cap ETF Vanguard Large-Cap ETF
Value	High book-to-market (value) firms offer greater returns than low book-to-market (growth) firms. Portfolio that goes long on value stocks and shorts growth stocks yields postive alpha.	Fama & French (1993); Lakonishok et al. (1994)	Vanguard Value ETF iShares Russell 1000 Value ETF Vanguard Growth ETF
Momentum	Stocks with high (low) past returns continue to have high (low) future returns. Portfolio that goes long on positive momentum stocks and shorts negative momentum stocks yields positive alpha.	Jegadees & Titman (1993); Carhart (1997)	iShares Edge MSCI USA Momentum ETF SPDR® Russell 1000 Momentum ETF
Low volatility	Stocks with low volatility (risk) offer higher returns in the long run than high volatility stocks. Portfolio that goes long on low volatility stocks and shorts high volatility stocks yields positive alpha.	Baker et al. (2011); Frazzini & Pedersen (2014)	iShares Edge MSCI USA Minimum Volatility ETF Invesco S&P 500 Low Volatility ETF

Factors provide attractive investments strategies for two main reasons:

1. They have been shown to offer persistent return premiums (alphas) and superior risk-adjusted performance in different time periods and across markets.
2. The average correlation of their returns (long-short portfolios) is close to zero which suggests potential diversification benefits across factor strategies.

Although most financial research uses factors to explain the cross-section of stock returns, some studies take a more practical approach and evaluate factors as investment strategies. For example, Israel & Moskowitz

(2013) study the performance and robustness of size, value, and momentum in the U.S. from 1926 to 2011 and find that long-short size, value and momentum portfolios have provided investors with 1.42%, 3.45% and 10.48% annualized CAPM alphas, respectively. Also low volatility strategies such as betting-against-beta of Frazzini & Pedersen (2013) produce a significant annualized alpha of 9.1% even after adjusting for market, size, and value exposure. Ilmanen & Kizer (2012) study the diversification benefits of factors and show that a portfolio of long-short factors exhibits a significant drop in volatility compared to individual factor portfolios. They also argue that factor diversification has been more effective than traditional asset-class diversification in general and especially during economic downturns. Despite these benefits there are major concerns for factor investing with real-life portfolios.

2.1.3 Concerns about factors and factor investing

Biggest concerns about factor investing relate to the role of short positions and implementation costs. Financial research studies factors mainly with long-short portfolios that face no transaction costs or other implementation constraints, which is far from what investors can achieve in the real world. Because of these concerns real-life factor portfolios' performance can be significantly different from the academic factor portfolios' which has major implications for the usefulness of factor investing.

The role of shorting is discussed in e.g. Israel & Moskowitz (2013) who find that long positions account for almost all of size, but only about half of value and momentum profits. Lack of short positions also leads to greater the market exposure i.e. the market factor becomes the main driver of portfolio returns (Ang, 2014), and the diversification benefits are more modest (Ilmanen & Kizer, 2012). On the other hand, short positions are costlier than long positions and some investors are restricted from shorting altogether (e.g. mutual funds). Taking short positions involves significant transaction costs, borrowing costs, margin requirements [4] and management fees which dent the portfolio's performance. Considering these issues, Blitz et al. (2014) actually suggest that the long-only approach would be optimal for factor investing in practice. Israel & Moskowitz (2013) conclude, too, that also the long-only portfolios on value and momentum deliver positive and significant alphas over the market portfolio and the raw returns of long-only size, value, and momentum portfolios dominate their long-short counterparts. Also, according to Ilmanen & Kizer (2012), factor diversification does not become obsolete even in the long-only context, and long-only portfolios provide exposure to the intended factors to some extent, albeit the significant market exposure (Ang, 2014; Israel & Moskowitz, 2013).

Other concerns for factor strategies' implementation relate to transaction costs, liquidity constraints and investment choices. The academic factor portfolios omit transaction costs and liquidity issues completely, which makes their performance misleading. For example, Jacobs & Levy (2014) argue that factor strategies require increased exposure to small capitalization stocks that are less liquid and command higher transaction

[4] In the U.S. the Federal Reserve's Regulation T requires investors to satisfy the Reg T margin at the end of each trading day. Reg T margin is 50% of the market value of short and long positions on the margin account i.e. investor must have this amount deposited as cash on the margin account.

costs. Similarly to Malkiel (2014), Jacobs & Levy also raise concerns about factor strategies' implementation as they involve many active decisions such as how to define the factor(s), what is the selection universe of securities, and how to weigh and rebalance the portfolios. These decisions lead to varying performance of factor portfolios aiming to capture the same factors and can result in unintended factor tilts. Jacobs & Levy (2014) also speculate that large-scale implementation of factor strategies by retail ETFs, for example, could result in the disappearance of factor premiums and factor crashes, but no evidence of this yet exists (Israel & Moskowitz, 2013). Despite these concerns, factor investing has seen a significant growth in popularity and also some researchers have turned their interest to real-life factor portfolios.

2.2 Factor investing in practice

This section covers the few studies on factor investing in practice and describes the U.S. factor ETF market and the ETFs studied in this paper. Real-life factor portfolios are mostly long-only, which has major implications for their performance and risk exposure. Despite these concerns, factor investing shows increasing interest among investors, and some factor strategies have proven to be beneficial also in real-life portfolios.

2.2.1 Literature review

To my knowledge only Gelderen & Huij (2014) and Glushkov (2015) have studied real-life factor portfolios more extensively. In their study of U.S. mutual funds over the period 1990 to 2010, Gelderen & Huij find that a significant number of funds (between 20 to 30%) have adopted factor investing strategies and funds following small cap, value, and low beta strategies outperform the market. However, there seems to be no premium for mutual funds following momentum strategies. Glushkov (2015) on the other hand evaluates U.S. smart beta ETFs' relative performance and factor exposure over the period 2003 to 2014. He finds mixed evidence of outperformance and only value and low volatility ETFs have beaten their risk-adjusted benchmarks. As for factor exposures, smart beta ETFs seem to offer exposure to the intended factors but also exhibit potentially unintended factor tilts (Glushkov, 2015). Also, Malkiel (2014) has analyzed a sample of smart beta ETFs but claims that factor investing in form of smart beta ETFs is more a testament to smart marketing than smart investing. He argues that retail ETFs aiming to capture factors and their return premiums command poor risk-adjusted performance in exchange for higher management fees. Another closely related study is by Tuokko (2017) who studies MSCI size, value, and momentum factor indexes and their usefulness for factor investing. He finds that all MSCI factor indexes have significant market exposure and therefore the intended factor exposures remain weak. Factor indexes' performance also seem to follow the long-only factor portfolios' and they do not provide clear diversification benefits. As most factor ETFs are based on factor indexes, Tuokko's (2017) findings have major implications for factor ETFs, too.

2.2.2 Factor ETFs

Factor ETFs that provide exposure to long- or short sides of academic factors are mostly passive index tracking funds intended for both retail and institutional investors. All major investment companies such as Blackrock, Vanguard, State Street Global Advisors, and Invesco offer factor ETFs and the scale and scope of the factor ETF market is great. The U.S. market is by far the largest and accounts for more than 80% of global factor ETF market (Morningstar, 2017), which is the reason this study focuses on U.S. factor ETFs. First U.S. factor ETFs were launched in 2000 and the factor ETF market has grown rapidly ever since, even faster than the broader ETF market and the asset-management industry as a whole (Morningstar, 2017). Size and value were among the first strategies to be implemented and throughout the 21st century more and more factor strategies have been offered through ETFs. Figure 1 plots the growth in net assets of a sample of factor ETFs investing in U.S. equities. Many factor ETF categories have attracted over $100 billion in net assets and the largest individual ETFs have market capitalizations of over $40 billion.

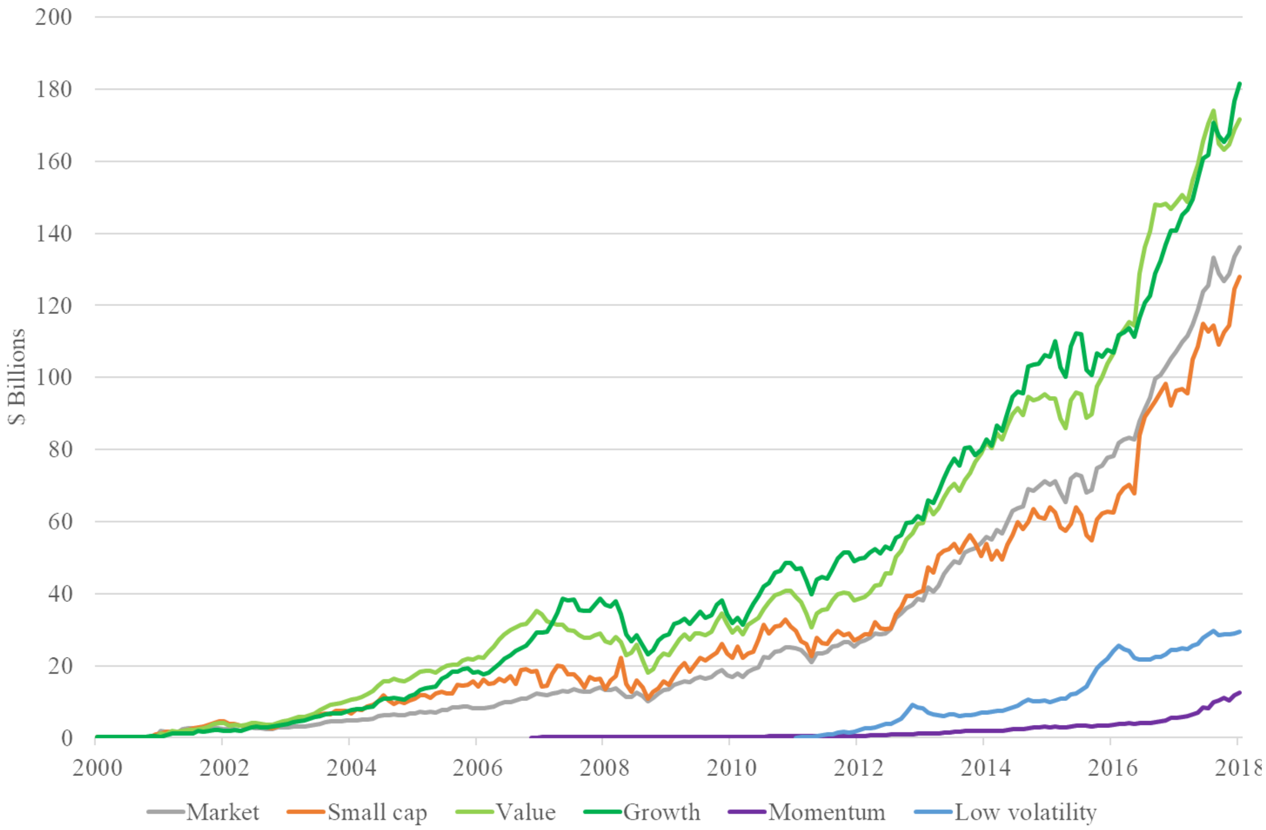

Figure 1 Net assets of U.S. factor ETFs.
This figure plots the total net assets ($ Billions) of U.S. factor ETFs. Each category is formed of ETFs following a similar investment strategy. Data is from CRSP and the sample period is from June 2000 to June 2018.

Table 2 presents summary statistics of the factor ETF categories studied in this paper including market ETFs, which are used as a reference group throughout the study. Size and value categories are split in two as both small and large cap[5], and value and growth ETFs are offered to investors. Size and value ETFs are the most common both in number and in net assets and they have the longest return history available, while momentum and low volatility ETFs are newer additions to the factor ETF market. Table 2 shows also that factor ETFs

[5] Although large cap ETFs are fairly similar to market ETFs, I study them separately as they provide exposure to only large cap stocks and thus the short side of the size factor. The first large cap ETF was launched already in 1993, but I study their performance only after June 2000 to ensure comparability.

command higher expense ratios than plain market ETFs, but overall the expense ratios are rather low. Similarly to academic literature, the factor ETF market goes well beyond these simple factors and, for example, investment research company Morningstar classifies factor ETFs (smart beta ETFs) into 19 different categories. Especially popular in numbers are also multifactor ETFs, which aim to capture multiple factors simultaneously, and yield oriented ETFs investing in high dividend yield stocks. These ETF categories are not covered in this study due to shorter return histories, less-focused investment strategies, and greater in-category variation.

Table 2 Summary statistics of U.S. factor ETFs.
This table presents summary statistics of the sample of U.S. factor ETFs. All categories are formed of active equity ETFs following a similar investment strategy. The data is from CRSP, Morningstar, and ETF factsheets, and the summary statistics are calculated based on observations from June 2018.

ETF category		**Number of ETFs**	**Net assets ($ Billions)**			**Inception**		**Expense ratios (ann.)**	
			Total	Average	Largest ETF	First ETF	Average age (years)	Average	Lowest
Market		7	136.1	19.4	97.4	May 2000	12.1	0.05 %	0.03 %
Size	Small cap	18	127.9	7.1	47.1	May 2000	8.6	0.12 %	0.05 %
	Large cap	14	620.2	44.3	259.3	Jan 1993	11.8	0.05 %	0.01 %
Value	Value	47	171.7	3.7	38.7	May 2000	10.3	0.15 %	0.04 %
	Growth	42	181.6	4.3	42.3	May 2000	10.9	0.16 %	0.04 %
Momentum		15	12.4	0.8	9.3	March 2007	3.2	0.24 %	0.12 %
Low volatility		27	29.4	1.1	14.7	May 2011	2.7	0.20 %	0.10 %

With ever-increasing popularity of factor ETFs, investors ought to know how these products really work and what are the major differences compared to academic factor portfolios. Research on factor ETFs and factor investing in practice also contributes to the vast academic literature on factors.

2.3 Contribution and research questions

This section presents the research questions I intend to answer in this study and discusses how my research relates to literature on factors and factor investing.

2.3.1 Contribution to existing literature

Most academic studies on factors do not consider how factor strategies perform in real-life portfolios. Since the academic zero-cost long-short factor portfolios are inherently different from what investors can achieve in the real world, it is important to evaluate factors also in this setting. I aim to provide evidence of factors and their performance in real-life portfolios that face implementation costs and other constraints, and also evaluate factor ETFs as an investment alternative. My research is most closely related to Glushkov (2015) but there are two major differences. First, I study a smaller set of factor ETF categories and do not follow Morningstar's smart beta classifications directly, whereas Glushkov covers 13 different categories, many with less than five example ETFs, and relies extensively on Morningstar's classifications. Second, my focus is on factor investing in practice and I evaluate the performance and risk exposure of factor ETFs relative to both long-short and long-only factor portfolios used in financial research. Glushkov on the other hand studies the relative performance of smart beta ETFs compared to other benchmarks and their factor exposures in standard regression setting. My exact research questions are discussed next.

2.3.2 Research questions

Considering the benefits of and concerns for factor investing, a major question raises: Do factor ETFs work as intended and is factor investing beneficial in practice? I tackle this problem with three research questions (RQ) which are formulated as follows:

RQ1: Is the performance of factor ETFs similar to the academic factor portfolios'?

- Factor portfolios have been shown to offer persistent return premiums and superior risk-adjusted performance. Can factor ETFs match their performance and are there any major differences?

RQ2: Do factor ETFs provide diversification benefits?

- Ilmanen and Kizer (2012) argue that factor diversification is superior to asset-class diversification. Are the correlations of factor ETFs as beneficial?

RQ3: Do factor ETFs provide exposure to the intended factors and are there any unintended factor tilts?

- Key to factor portfolios' performance is the low market exposure and high exposure to the intended factor(s). Are factor ETFs able to achieve the intended factor exposures?

Next chapter describes the data and research methodology. Results are presented in chapter 4.

3. Data and research methodology

This chapter describes the sample selection and ETF classification, the data of ETFs and risk factors, and presents the research methodology.

3.1 Sample selection and ETF classification

I form the factor ETF sample using data from Morningstar and the information provided in individual ETF's factsheets and websites. Using Morningstar's ETF screener [6] to screen for U.S. equity ETFs leaves me with a sample of 454 funds. I then categorize the ETFs to factor and non-factor ETFs and further divide the factor ETFs to groups with a similar investment strategy. Importantly, I use a broad definition for a factor ETF: Factor ETF is any ETF that provides exposure to long- and/or short sides of factor(s) studied in academic literature. Altogether there are 325 U.S. equity ETFs that can be classified as factor ETFs. The ETFs left out of the sample consist mainly of sector, thematic, and purely active ETFs. Note also that the sample consists of active ETFs

[6] https://www.morningstar.com/tools/etf-screener.html

only, so it is prone survivorship bias. Table A1 in Appendix A lists all the ETFs, their ticker symbols, inception years, and net assets as of June 2018 in the factor ETF categories. The exact definitions used to categorize factor ETFs to these categories are as follows:

- Market ETFs: Provide exposure to the total stock market. In practice these include ETFs with an investment universe of Russell 3000 stocks or broader.
- Size ETFs: Provide exposure to small or large capitalization stocks. Large capitalization ETFs invest in Russell 1000 or larger stocks and small capitalization ETFs in Russell 2000 or smaller stocks.
- Value ETFs: Provide exposure to value or growth stocks[7]. Value ETFs invest in stocks that display value characteristics such as low price/book and price/earnings ratios and growth ETFs invest in stocks that display growth characteristics such as high price/book and price/earnings ratios.
- Momentum ETFs: Provide exposure to stocks with higher price momentum and returns relative to other stocks over the past months/years.
- Low volatility ETFs: Select stocks based on their historical return volatility aiming to minimize the portfolio's total volatility.

3.2 Data of ETFs and risk factors

Data of ETF returns and net assets are from CRSP where each ETF is found based on the exchange ticker. For each factor ETF in the sample I use monthly holding period returns that include all distributions. Net assets are proxied with market capitalization (share price × shares outstanding) in the last trading day of each month. Table 3 shows the number of ETFs in each category and new ETF launches each year. First value, size and market ETFs were launched in May 2000, first momentum ETFs in March 2007, and first low volatility ETFs in May 2011. Although size and value ETFs are largest by market capitalization, momentum and low volatility categories have seen the most ETF launches in the past few years.

Table 3 Number of factor ETFs and new ETF launches.
This table reports the number of ETFs (in bold) and new ETFs launches (in italics) by category each year.

ETF category		**2000**	**01**	**02**	**03**	**04**	**05**	**06**	**07**	**08**	**09**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**06/2018**
Market		**3**	**4**	**4**	**4**	**5**	**5**	**5**	**5**	**5**	**6**	**7**	**7**	**7**	**7**	**7**	**7**	**7**	**8**	**8**
		3	*1*			*1*					*1*	*1*							*1*	
Size	Small cap	**2**	**2**	**2**	**2**	**4**	**7**	**8**	**8**	**8**	**9**	**11**	**11**	**11**	**13**	**13**	**13**	**14**	**18**	**18**
		2				*2*	*3*	*1*			*1*	*2*			*2*			*1*	*4*	
	Large cap	**3**	**3**	**3**	**3**	**5**	**6**	**6**	**7**	**9**	**11**	**13**	**13**	**13**	**13**	**13**	**13**	**13**	**14**	**14**
		3				*2*	*1*		*1*	*2*	*2*	*2*							*1*	
Value	Value	**8**	**9**	**9**	**9**	**14**	**18**	**22**	**24**	**25**	**26**	**32**	**35**	**36**	**37**	**39**	**40**	**41**	**46**	**47**
		8	*1*			*5*	*4*	*4*	*2*	*1*	*1*	*6*	*3*	*1*	*1*	*2*	*1*	*1*	*5*	*1*
	Growth	**8**	**9**	**9**	**9**	**14**	**18**	**22**	**24**	**25**	**26**	**32**	**35**	**35**	**35**	**36**	**36**	**38**	**42**	**42**
		8	*1*			*5*	*4*	*4*	*2*	*1*	*1*	*6*	*3*			*1*		*2*	*4*	
Momentum									**1**	**1**	**1**	**1**	**1**	**3**	**4**	**5**	**6**	**10**	**14**	**15**
									1					*2*	*1*	*1*	*1*	*4*	*4*	*1*
Low volatility													**2**	**2**	**6**	**7**	**11**	**19**	**26**	**27**
													2		*4*	*1*	*4*	*8*	*7*	*1*

[7] There is some overlap with size and value strategies as many value and growth ETFs invest in small or large cap stocks exclusively. Combining all value (growth) ETFs in the same category should however weaken the effect from size tilts.

Data of risk factors is from Kenneth French's data library[8]. I make extensive use of the monthly Fama-French research factors Mkt-Rf, SMB, HML, CMA, and RMW, and the momentum factor WML for the U.S. The risk-free rate used to calculate the excess returns of the ETF portfolios is also from Kenneth French's data library. The exact methodology of Fama-French research factors is discussed in e.g. Fama & French (2015) and the momentum factor in Carhart (1997). In addition to these risk factors, I use proxy for volatility factor VOL whose construction is explained in Appendix B[9]. SMB, HML, CMA, RMW, WML, and VOL are all long-short equity portfolios that provide a proxy for the risk factors. I also construct long-only versions of size (small and large capitalization stocks), value (value and growth stocks), momentum, and low volatility factors by applying the methodology of Fama-French research factors (Fama & French, 1993; 2015) and Carhart's (1997) momentum factor. Formation of the long-only factor portfolios is explained more in Appendix B.

3.3 Research methodology

To evaluate the performance and risk exposure of U.S. factor ETFs, I use several statistical methods and perform robustness tests when possible. I begin by calculating key figures of performance for all factor ETFs and long-short and long-only factors and also evaluate their co-movement. Then I perform regression analysis with different specifications for all factor ETFs and categories.

3.3.1 Performance measures and co-movement

Key figures of performance include average monthly and annual returns, their volatilities, and risk-adjusted performance measures. Annualized returns and volatilities are estimated from the monthly observations and I also study the cumulative returns of factor ETFs and factor portfolios. Sharpe ratio (Sharpe, 1964) is used to get simple estimates of the risk-adjusted performance. In addition, I evaluate the CAPM alpha and beta from equation (1) which tell about the market-adjusted performance.

To evaluate the diversification benefits of factor ETFs and their co-movement with long-short and long-only factor portfolios, I estimate the correlation of their monthly returns. The correlations help explain the similarities and differences in performance and give background to evaluate the results from the regression analyses. I also evaluate the long-short and long-only factors beginning from the launch of the first factor ETFs following them as a reference case.

3.3.2 Regression analyses

The main research method of the study are time-series regression analyses with different specifications. In these analyses the monthly excess returns of factor ETFs and ETF categories are regressed on the monthly excess returns of risk factors. Following Israel & Ross (2017), I only evaluate ETFs with at least 36 monthly return observations, but all ETFs are included in the value- and equally-weighted portfolios of factor ETFs.

[8] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[9] I thank Petri Jylhä for providing data to construct a proxy for the volatility factor.

The main regressions used are the CAPM and Fama-French-Carhart regressions. Analyses using long-only risk factors and Fama-French five-factors function as robustness tests. Importantly, I am interested in the factor exposures, their statistical significance, and the explanatory power of these regression models. As Israel & Ross (2017) point out, it is important to evaluate both the factor exposure (beta) and its statistical significance since only economically meaningful and statistically significant factor exposures can be deemed to affect the performance to an important extent. The explanatory power measured with (adjusted) R-squared tells how much of the returns are explained by the factors and allows to compare different regression models. A model with a higher (adjusted) R-squared describes the risk exposure better are is therefore preferable.

First, the regression based on the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) tells about the market exposure of factor ETFs and highlights the possible abnormal return (alpha). CAPM regression uses the regression equation (1) where $r_{it} - r_{Ft}$ is the excess return of the security or portfolio i, a_i is the intercept (alpha), b_i is market beta, Mkt_t is the excess return of a value-weighted market portfolio, and e_{it} is the error term to capture all variation not explained by b_i.

$$r_{it} - r_{Ft} = a_i + b_i Mkt_t + e_{it} \tag{1}$$

The second main regression (2) follows the Fama-French-Carhart (1997) model that adds the size, value, and momentum factors. SMB_t is the difference between returns of small and big stocks, HML_t is the difference between high and low book-to-market stocks, and WML_t is the difference between stocks that had high returns in the past $t - 12$ to $t - 2$ months (winners) and stock that had low returns in the past $t - 12$ to $t - 2$ months (losers). s_i, h_i, and w_i capture the portfolio's exposure to size, value, and momentum factors, respectively.

$$r_{it} - r_{Ft} = a_i + b_i Mkt_t + s_i SMB_t + h_i HML_t + w_i WML_t + e_{it} \tag{2}$$

As a robustness test, I run the Fama-French-Carhart (1997) regression using long-only factor portfolios. The long-only regression equation (3) is the same as (2) except SMB_t, HML_t, and WML_t are replaced with $Small\ Cap_t, Value_t$, and $Winners_t$ time-series, respectively. As all factor ETFs are long-only, this regression should highlight the factor exposures and possibly have a higher explanatory power.

$$r_{it} - r_{Ft} = a_i + b_i Mkt_t + s_i\, Small\ Cap_t + \ h_i\, Value_t \ + \ w_i\, Winners_t + e_{it} \tag{3}$$

The second robustness regression uses the Fama-French five-factor model (Fama & French, 2015) which replaces the momentum factor with profitability and investment factors. In the regression equation (4) RMW_t is the difference between stocks with robust and weak profitability, and CMA_t the difference between stocks of low and high investment firms. r_i and c_i capture the exposure to profitability and investment factors. This model might have better explanatory power than the previous models and reveal some new risk exposures of factor ETFs.

$$r_{it} - r_{Ft} = a_i + b_i Mkt_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it} \tag{4}$$

4. Results and discussion

In the following sections I present my key results and answers to the research questions, discuss how they relate to the earlier research, and point out the limitations of my study.

4.1 Performance of factor ETFs

I first examine the performance of U.S. factor ETFs relative to both long-short and long-only factor portfolios and also compared to market ETFs (RQ1). Then I discuss their potential diversification benefits (RQ2). Performance of factor ETFs seems to follow that of long-only factor portfolios and is significantly better than that of long-short factors. The diversification benefits are more modest but factor ETFs seem to offer better diversification than their respective long-only factor portfolios. These results are discussed next.

4.1.1 Performance compared to long-short and long-only factor portfolios

I begin by looking at the cumulative returns of factor ETFs and factor portfolios. Figure 2 plots the cumulative returns of value-weighted ETF portfolios compared to the respective long-short and long-only factors. Each panel also includes market ETFs as a reference group. Figure 2 highlights three main results. First, factor ETFs seem to follow the performance of long-only rather than long-short factor portfolios and indeed the correlations between factor ETFs and long-only portfolios average 0.95 compared to only 0.11 with long-short portfolios. Only the long-only small cap factor portfolio performs significantly better than the small cap ETFs and the cumulative returns of long-short portfolios fall behind factor ETFs in all categories. These results are consistent with Israel & Moskowitz (2013), who show that the raw returns of long-short portfolios on size and value are dominated by the contribution from long positions. Second, looking at factor ETFs' performance relative to market ETFs', only small cap and value have clearly beaten market ETFs over the respective sample period. Although Ang (2014) argued that market exposure is the main driver of returns for long-only factor portfolios, tilting the portfolio towards small or value stocks does seem to have a notable effect on the portfolios' performance. Third, comparison of size and value ETFs in panels A – D also reveals that small cap ETFs have higher cumulative returns than large cap ETFs and that value has higher returns than growth. This is consistent with academic studies on size and value premiums (see e.g. Fama & French, 1993). Overall, Figure 2 shows that market ETFs behave very similarly to factor ETFs, especially for large cap, growth, momentum, and low volatility factors, which has implication for diversification benefits and factor exposures studied later.

To further examine the performance of factor ETFs and portfolios, I calculate common performance measures. Table 4 shows the annualized average returns and standard deviations, Sharpe ratios, and CAPM alphas and betas of the portfolios in different factor categories. Long-short and long-only factor portfolios use the same sample periods as their respective factor ETFs to make their comparison easier. Note also that momentum and low volatility have shorter return histories, which exclude the depression in stock prices in the beginning of the 21st century and the financial crisis 2008-2009 for low volatility. Overall, Table 4 highlights five key results.

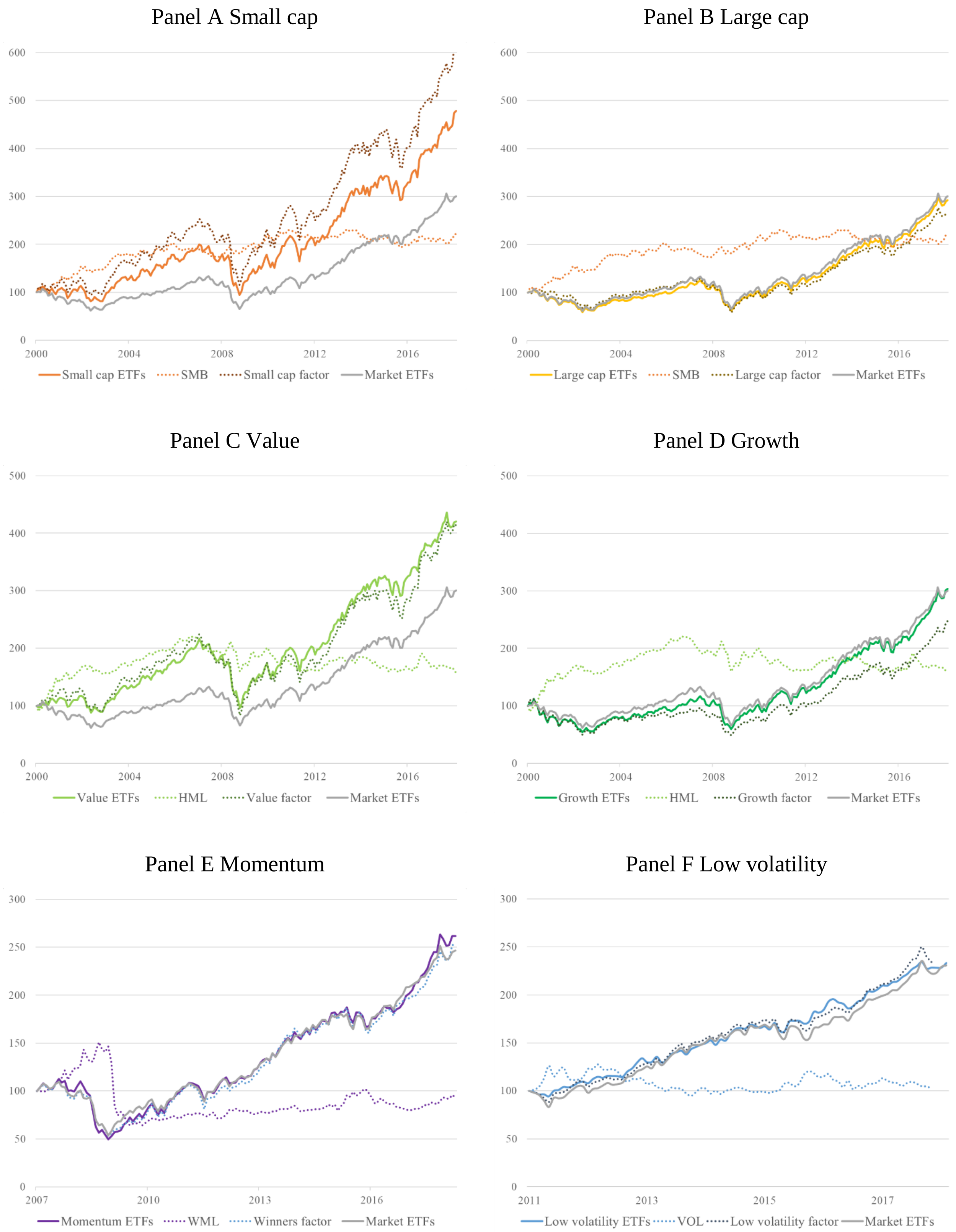

Figure 2 Cumulative returns of U.S. factor ETFs and long-short and long-only factor portfolios.
This figure plots the cumulative returns of U.S. factor ETFs (value-weighted portfolios) beginning from the launch of the first ETF in each category till June 2018. It also plots the returns of long-short and long-only factor portfolios related to each ETF category and the market ETFs as a reference group.

First, beginning with raw average returns and volatility, factor ETFs' performance is similar to long-only factors' but differs significantly from long-short portfolios'. For example, value ETFs' monthly (annual) average returns, 0.76% (8.27%), are close to value long-only portfolios returns, 0.80% (8.16%) whereas HML returns are only 0.25% (2.54%) under the same sample period. Only small cap and growth ETFs deviate more from their respective long-only factor pairs which was highlighted also in Figure 2. Factor ETFs offer similar volatility as long-only factor portfolios, which is higher than long-short portfolios', though. Second, looking at risk-adjusted performance, factor ETFs and long-only factor portfolios have similar Sharpe ratios and clearly beat their long-short counterparts. Only SMB factor portfolio comes close to its long-only alternatives on a risk-adjusted basis. These results support Blitz et al. (2014), who argue that long-only factor investing might be preferable with real-life portfolios: Investors, who only care about raw returns would prefer the long-only alternatives.

Table 4 Performance of U.S. factor ETFs, long-short and long-only factor portfolios.
This table reports annualized performance measures of value-weighted portfolios of U.S. factor ETFs and long-only and long-short factor portfolios. Sample period ends in June 2018 for all categories.

	Small cap			**Large cap**		
Annualized	ETFs	Long-only	SMB	ETFs	Long-only	SMB
Average return	9.04 %	10.63 %	4.52 %	6.11 %	5.51 %	4.52 %
Standard deviation	18.49 %	19.36 %	9.20 %	14.42 %	15.05 %	9.20 %
Sharpe ratio	0.40	0.47	0.32	0.31	0.26	0.32
CAPM alpha	2.37 %	3.86 %	2.32 %	-0.06 %	-0.64 %	2.32 %
(t-statistic)	(1.322)	(1.873)	(1.103)	(-0.131)	(-0.703)	(1.103)
CAPM beta	1.14	1.17	0.18	0.96	0.98	0.18
	Value			**Growth**		
Annualized	ETFs	Long-only	HML	ETFs	Long-only	HML
Average return	8.27 %	8.16 %	2.54 %	6.33 %	5.14 %	2.54 %
Standard deviation	15.23 %	18.62 %	10.48 %	16.46 %	17.57 %	10.48 %
Sharpe ratio	0.44	0.35	0.10	0.29	0.20	0.10
CAPM alpha	2.15 %	1.77 %	1.73 %	-0.22 %	-1.46 %	1.73 %
(t-statistic)	(1.652)	(0.850)	(0.695)	(-0.266)	(-1.245)	(0.695)
CAPM beta	0.96	1.11	-0.03	1.09	1.14	-0.03
	Momentum			**Low volatility**		
Annualized	ETFs	Long-only	WML	ETFs	Long-only	VOL
Average return	8.92 %	8.59 %	-0.61 %	12.71 %	13.27 %	0.38 %
Standard deviation	16.82 %	17.03 %	16.75 %	8.25 %	10.15 %	13.39 %
Sharpe ratio	0.49	0.46	-0.07	1.51	1.28	0.01
CAPM alpha	0.30 %	-0.26 %	3.86 %	5.52 %	2.13 %	10.03 %
(t-statistic)	(0.154)	(-0.147)	(0.799)	(2.430)	(2.268)	(2.195)
CAPM beta	1.04	1.07	-0.39	0.54	0.86	-0.68

	Market		**Sample starts**	
Annualized	ETFs	Mkt	Small cap	June 2000
Average return	6.27 %	6.33 %	Large cap	June 2000
Standard deviation	14.61 %	14.82 %	Value	June 2000
Sharpe ratio	0.32	0.32	Growth	June 2000
CAPM alpha	0.02 %	0.00 %	Momentum	April 2007
(t-statistic)	(0.0665)	(2.790)	Low volatility	June 2011
CAPM beta	0.98	1.00	Market	June 2000

Third, as for factor ETFs' performance compared to market ETFs', small cap and value have offered higher returns and better risk-adjusted performance than market ETFs. Table 4 does not directly allow the comparison of momentum, low volatility and market ETFs, but using the same sample periods I find that the returns of momentum and low volatility ETFs do not deviate significantly from market ETFs'[10]. Low volatility ETFs do in fact offer significantly lower volatility which leads to superior risk-adjusted performance. Observations from Table 4 contradict with Malkiel's (2014) claims that factor ETFs offer worse risk-adjusted performance than the market. On the contrary, their performance is equally good or better than market ETFs'.

Fourth, looking at the market-adjusted returns i.e. CAPM alphas, only long-short VOL and WML outperform their long-only counterparts and apart from small cap ETFs, factor ETFs have higher alphas than their long-only factor counterparts. In theory, factor ETFs' alphas should show signs of management fees and other costs, but not even market ETFs show support for this. Factor ETF alphas do, however, show signs of factor premiums: small cap and value ETFs have significantly higher alphas than large cap and growth ETFs, for example. Interestingly, low volatility ETFs and factor portfolios have the highest alphas that are also the only ones statistically significant over the short sample period. These results are consistent with Glushkov (2015) who finds significant alphas in value and volatility ETFs and Gelderen & Huij (2014) who find significant alphas small cap, value, and low beta mutual funds. Finally, looking at the CAPM betas, the long-short portfolios clearly have the lowest exposure to the market whereas the long-only factor ETFs and factor portfolios have betas around 1[11]. As discussed in Ilmanen & Kizer (2012) the low market exposure is the key to factor portfolios' performance and could provide diversification benefits. Comparison of factor ETFs' and factor portfolios' performance in Table 4, however, implies that long-only alternatives would be better. In Appendix C, I also report the results for equally-weighted portfolios of factor ETFs. Table A2 in Appendix C shows that the results for equally-weighted portfolios are similar to the value-weighted.

To conclude, the answer to RQ1 can be summarized as follows. Factor ETFs' performance is similar to the long-only factor portfolios' and differs significantly from the long-short portfolios'. Although the long-short portfolios have higher market alpha and lower beta, factor ETFs' returns and risk-adjusted performance is better, which gives support for the long-only approach to factor investing.

4.1.2 Diversification benefits

To study the diversification benefits of factor ETFs and factor portfolios, I estimate the correlations of their monthly returns. Table 5 reports the correlation matrix of value-weighted factor ETF portfolios and Table A3 in Appendix C the correlations of equally-weighted portfolios. As expected, the correlations of factor ETFs are high and average 0.86 for value-weighted and 0.89 for equally-weighted portfolios. Surprisingly, even small cap and large cap, and value and growth ETFs have high correlations with each other at 0.88 respectively,

[10] Market ETFs' annual returns (volatility), and Sharpe ratios starting from April 2007 have been 8.35% (15.10%) and 0.51 and from June 2011 onwards 12.53% (11.27%) and 1.09. Results are similar with equally-weighted portfolios.
[11] I discuss the market exposure of factor ETFs more in section 4.2.

although they aim to capture the total opposites of size and value factors. Also worth highlighting are the factor ETFs' high correlations with market ETFs which explains their similar performance and high betas shown in Table 4. Apart from these similarities, low volatility ETFs seem exceptional: their correlations with other factor ETF categories are lower at 0.71 and 0.81 on average for value- and equally-weighted portfolios respectively.

Table 5 Correlations of U.S. factor ETFs.
This table reports the correlations of monthly returns of value-weighted factor ETF portfolios.

ETF category		Market	Small cap	Large cap	Value	Growth	Momentum	Low volatility
Market		1.00						
Size	Small cap	0.91	1.00					
	Large cap	0.99	0.88	1.00				
Value	Value	0.95	0.93	0.92	1.00			
	Growth	0.97	0.91	0.96	0.88	1.00		
Momentum		0.93	0.86	0.92	0.87	0.96	1.00	
Low volatility		0.75	0.61	0.75	0.73	0.71	0.70	1.00

These results give some support for Ilmanen and Kizer (2012), who argue that factor diversification is meaningful in the long-only context as well. As a reference case, Table A6 in Appendix D reports the correlations of long-short and long-only factor portfolios for the same sample period as with factor ETFs. Similarly to Ilmanen and Kizer (2012), long-short factors show clear diversification benefits as their correlations are -0.17 on average, with volatility and size factors offering the lowest correlation at -0.67. Surprisingly, the correlations of long-only factor portfolios are higher than factor ETFs' at 0.91 on average. Not one long-only factor has a significantly lower correlation with other factors which implies poorer diversification benefits. As for the RQ2, I conclude that factor ETFs offer some diversification benefits as shown by the lower correlations, but they are not nearly as beneficial as with long-short factor portfolios.

4.2 Risk exposure of factor ETFs

To study RQ3, I begin by running the CAPM and Fama-French-Carhart regressions on the value- and equally-weighted factor ETF portfolios and all ETFs individually. As a robustness test, I study the ETFs also with long-only version of the Fama-French-Carhart model, and the Fama-French five-factor model. Regression results show that all factor ETFs have significant market exposure, but they do offer the intended factor tilts rather consistently. Only low volatility ETFs seem to have a significant alpha and established factor models cannot fully explain their performance. This section discusses these results.

4.2.1 Results from CAPM and Fama-French-Carhart regressions

Table 6 reports the regression results from the CAPM and Fama-French-Carhart regressions on the monthly returns of value-weighted factor ETF portfolios. Beginning with the CAPM regression, three main results can be highlighted. First, all ETF categories show significant exposure to the market factor, especially market, large cap, and growth ETFs. This is expected as all factor ETFs are long-only, which promotes their co-movement with the market. Small cap ETFs have the highest market beta at 1.139, but apart from low volatility ETFs, factor ETFs' betas are all close to 1. Interestingly, low volatility ETFs have the lowest beta at only 0.536 and CAPM manages to explain only about half of its performance. Second, looking at the CAPM alphas, only low volatility ETFs have a significant annual alpha of 5.52%. Other ETF categories show variation in alphas which is however consistent with the factor premiums. Finally, apart from low volatility ETFs, CAPM manages to explain most of the returns of factor ETFs but leaves some room for improvement.

Table 6 Results from CAMP and Fama-French-Carhart regressions.
This table shows the regression results from CAPM and Fama-French-Carhart regressions using monthly value-weighted returns of ETF portfolios starting from the launch of the first ETF in each category. Alphas of both models are annualized and the t-statistics are presented below the coefficients in italics. Sample ends in June 2018 for all ETF categories.

ETF category		**Obs.**	**CAPM**			**Fama-French-Carhart Model**					
			Alpha	Mkt-Rf	R^2	Alpha	Mkt-Rf	SMB	HML	WML	Adj. R^2
Market		217	**0.02 %**	**0.981**	0.991	**0.01 %**	**0.982**	**-0.032**	**0.062**	**-0.013**	0.993
			0.066	*153.203*		*0.039*	*155.861*	*-3.366*	*7.859*	*-2.531*	
Size	Small cap	217	**2.37 %**	**1.139**	0.837	**-1.08 %**	**1.014**	**0.773**	**0.115**	**0.021**	0.983
			1.322	*33.239*		*-1.869*	*79.795*	*40.807*	*7.179*	*2.106*	
	Large cap	217	**-0.06 %**	**0.964**	0.982	**0.49 %**	**0.980**	**-0.134**	**0.019**	**-0.017**	0.989
			-0.131	*108.418*		*1.327*	*122.702*	*-11.263*	*1.859*	*-2.711*	
Value	Value	217	**2.15 %**	**0.957**	0.873	**0.35 %**	**0.930**	**0.160**	**0.401**	**-0.022**	0.965
			1.652	*38.465*		*0.508*	*62.418*	*7.213*	*21.325*	*-1.865*	
	Growth	217	**-0.22 %**	**1.085**	0.954	**-0.04 %**	**1.057**	**0.142**	**-0.242**	**0.010**	0.981
			-0.266	*67.139*		*-0.070*	*87.918*	*7.936*	*-15.975*	*1.067*	
Momentum		135	**0.30 %**	**1.038**	0.856	**-1.34 %**	**1.124**	**0.114**	**-0.221**	**0.167**	0.902
			0.154	*28.114*		*-0.839*	*32.709*	*1.905*	*-3.893*	*5.306*	
Low volatility		85	**5.52 %**	**0.536**	0.542	**4.05 %**	**0.605**	**-0.160**	**-0.026**	**0.145**	0.588
			2.430	*9.907*		*1.865*	*11.035*	*-2.075*	*-0.294*	*2.334*	

Fama-French-Carhart model (FFC) that adds the size, value, and momentum factors explains the returns slightly better especially for small cap, value and momentum ETFs, and, more importantly, gives evidence of factor ETFs' intended and unintended factor exposures. For starters, small cap ETFs show significantly positive and large cap ETFs significantly negative exposure to the SMB factor, and similarly value ETFs show significantly positive and growth ETFs significantly negative exposure to the HML factor. Also, momentum ETFs have significant positive exposure to WML factor. However, despite these intended factor tilts market exposure becomes more significant for all factor ETF categories and there are signs of unintended factor tilts, albeit they are smaller and less significant than the intended. For example, both value and growth ETFs have a positive and highly significant loading on SMB factor and similarly small cap ETFs have a significant loading on the HML factor. These observations are consistent with Glushkov (2015) who finds that most smart beta ETFs exhibit potentially unintended factor tilts but show robust co-movement with their respective factors. Lastly, factor ETFs' alphas become much smaller and none of them remains statistically significant at a 5 % level. Fama-French-Carhart model still fails to fully explain low volatility ETFs' performance. Table A4 in

Appendix C reports the results for equally-weighted factor ETF portfolios. As their results do not significantly differ from that of value-weighted portfolios, I will not discuss them separately.

The unintended factor exposures shown in Table 6 raise concerns: Is this a systematic property of factor ETFs or is there significant in-category variation? Table 7 reports the share of ETFs within each category with a statistically significant positive (+) or negative (−) CAPM and FFC alpha, and factor loading on Mkt-Rf, SMB, HML, and WML (at a 5% level). Note that only the ETFs with at least 36 months of return observations are included in this analysis to get more reliable estimates. Beginning with alphas, only a handful of ETFs have a statistically significant positive CAPM alpha and no ETF has a significant positive FFC alpha. All ETFs studied here have a significantly positive exposure to the market factor, which was highlighted in the exceptionally high t-statistics for the market factor in Table 6. Most small cap, large cap, value, and growth ETFs offer the intended factor exposure and all momentum ETFs have a significantly positive loading on WML. There is however significant in-category variation with the unintended factor tilts: for example, some value and growth ETFs have significant positive or negative exposure to the size factor, and many value ETFs load negatively and growth ETFs positively on the WML factor. These findings are consistent with Jacobs & Levy (2014) and Malkiel's (2014) observations that factor strategies can be implemented in many ways which might lead to unintended factor tilts. Some of the variation can also rise from the ETF classifications as is discussed further in section 4.3. Table 6 shows also that only some low volatility ETFs have exposure to SMB, HML, and WML, which supports the finding that FFC-model cannot fully explain their performance.

Table 7 Statistically significant alphas and factor exposures.
This table shows the share of ETFs (%) with statistically significant positive (+) or negative (−) CAPM and Fama-French-Carhart (FFC) alphas, and exposure to market, size, value, and momentum factors. ETFs analyzed have at least 36 months of return observations and samples end in June 2018 for all categories.

ETF category		No. of ETFs	CAPM Alpha		FFC Alpha		Mkt-Rf		SMB		HML		WML	
			+	−	+	−	+	−	+	−	+	−	+	−
Market		6	0.0 %	0.0 %	0.0 %	0.0 %	100 %	0.0 %	0.0 %	50.0 %	50.0 %	0.0 %	0.0 %	16.7 %
Size	Small cap	13	7.7 %	7.7 %	0.0 %	30.8 %	100 %	0.0 %	92.3 %	0.0 %	46.2 %	0.0 %	30.8 %	23.1 %
	Large cap	13	7.7 %	0.0 %	0.0 %	0.0 %	100 %	0.0 %	0.0 %	92.3 %	38.5 %	7.7 %	0.0 %	23.1 %
Value	Value	39	5.1 %	0.0 %	0.0 %	0.0 %	100 %	0.0 %	53.8 %	25.6 %	97.4 %	0.0 %	2.6 %	38.5 %
	Growth	36	2.8 %	2.8 %	0.0 %	8.3 %	100 %	0.0 %	61.1 %	27.8 %	0.0 %	83.3 %	47.2 %	16.7 %
Momentum		5	0.0 %	0.0 %	0.0 %	20.0 %	100 %	0.0 %	40.0 %	20.0 %	0.0 %	60.0 %	100 %	0.0 %
Low volatility		10	10.0 %	0.0 %	0.0 %	0.0 %	100 %	0.0 %	40.0 %	20.0 %	40.0 %	0.0 %	40.0 %	0.0 %

In conclusion, RQ3 can be summarized as follows. Factor ETFs offer the intended factor exposures rather consistently but the market exposure remains significant. Many ETFs also have unintended factor tilts, which might affect their performance. Low volatility ETFs are exceptional and their performance cannot fully be explained by market, size, value, and momentum exposures.

4.2.2 Additional tests with long-only portfolios and Fama-French five-factor model

Regression analyses with long-only factor portfolios and the Fama-French five-factor model aim to better explain the factor ETFs' risk exposures and give support for the findings for RQ3. Table 8 shows these regression results for the value-weighted factor ETF portfolios. Beginning with the long-only version of the Fama-French-Carhart model, the model seems to explain ETFs' returns only marginally better than the standard FFC model in Table 6. Factor ETFs' direct exposure to the market factor becomes less significant, especially for small cap ETFs, as long-only factors also capture some of the variation in market returns. ETFs' alphas are mostly similar to FFC model, except that low volatility ETFs now have a statistically significant alpha. Long-only factor portfolios should capture factor ETFs' risk exposures better as factor ETFs too are long-only and, indeed, small-cap, value, and momentum ETFs show more significant exposure to the intended factors. The unintended factor exposures still remain but are less significant on average. Interestingly, low volatility ETFs now have significant exposure only to the market factor and the long-only FFC model cannot explain their performance any better. Overall, the long-only FFC model does not change the results for RQ3.

Table 8 Regression analyses with long-only FFC and Fama-French five-factor models.
This table shows the regression results from Fama-French-Carhart model with long-only factors and Fama-French five-factor model. Alphas of both models are annualized and the t-statistics are presented below the coefficients in italics. Sample periods and number of observations are the same as in CAPM and FFC regressions in Table 6.

ETF category		**Fama-French-Carhart Model Long-Only**						**Fama-French Five-Factor Model**						
		Alpha	Mkt-Rf	Small cap	Value	Winners	Adj. R^2	Alpha	Mkt-Rf	SMB	HML	RMW	CMA	Adj. R^2
Market		**0.02 %**	**0.970**	**-0.056**	**0.097**	**-0.030**	0.993	**-0.47 %**	**1.006**	**-0.022**	**0.045**	**0.052**	**0.012**	0.994
		0.062	*64.988*	*-3.394*	*7.155*	*-2.150*		*-1.605*	*145.872*	*-2.249*	*4.327*	*4.272*	*0.784*	
Size	Small cap	**-0.94 %**	**0.127**	**0.787**	**-0.002**	**0.093**	0.985	**-1.17 %**	**1.012**	**0.780**	**0.099**	**0.025**	**0.011**	0.983
		-1.726	*4.554*	*25.647*	*-0.061*	*3.556*		*-1.905*	*70.177*	*39.001*	*4.540*	*0.989*	*0.351*	
	Large cap	**0.46 %**	**1.117**	**-0.139**	**0.054**	**-0.050**	0.989	**-0.12 %**	**1.010**	**-0.121**	**0.001**	**0.068**	**0.004**	0.989
		1.234	*59.343*	*-6.708*	*3.167*	*-2.804*		*-0.325*	*115.366*	*-9.923*	*0.100*	*4.375*	*0.191*	
Value	Value	**0.65 %**	**0.450**	**-0.033**	**0.541**	**-0.050**	0.960	**-1.03 %**	**0.993**	**0.178**	**0.302**	**0.116**	**0.166**	0.971
		0.885	*12.052*	*-0.802*	*15.989*	*-1.418*		*-1.567*	*64.569*	*8.339*	*12.981*	*4.235*	*4.979*	
	Growth	**-0.30 %**	**1.097**	**0.299**	**-0.384**	**0.061**	0.979	**0.17 %**	**1.047**	**0.153**	**-0.197**	**0.021**	**-0.126**	0.982
		-0.534	*37.810*	*9.346*	*-14.590*	*2.229*		*0.312*	*80.753*	*8.488*	*-10.038*	*0.902*	*-4.471*	
Momentum		**-0.70 %**	**0.740**	**-0.111**	**-0.224**	**0.669**	0.913	**-1.13 %**	**1.079**	**0.117**	**-0.302**	**0.039**	**-0.085**	0.880
		-0.461	*7.009*	*-1.062*	*-2.545*	*7.107*		*-0.617*	*27.021*	*1.700*	*-4.270*	*0.369*	*-0.690*	
Low volatility		**4.94 %**	**0.885**	**-0.025**	**-0.254**	**-0.024**	0.572	**4.14 %**	**0.637**	**-0.088**	**-0.381**	**0.234**	**0.672**	0.687
		2.254	*5.038*	*-0.144*	*-1.624*	*-0.134*		*2.188*	*13.224*	*-1.170*	*-4.235*	*2.061*	*4.934*	

Looking at the Fama-French five-factor (FF5) results, the explanatory power is not significantly better, but the model does reveal some new factor exposures and explains low volatility ETFs' performance slightly better. Similarly to the Fama-French-Carhart model, the market exposure of factor ETFs is more significant than with the long-only factor portfolios, and the intended factor exposures for small and large cap, and value and growth ETFs remain. FF5 model also reveals that value ETFs have significant positive exposure to both profitability (RWM) and investment (CMA) factors implying that they invest in firms with robust profitability and low investment spending. Growth ETFs on the contrary have significantly negative exposure to the CMA factor. Removing the WML factor lessens the model's explanatory power for momentum ETFs but improves the explanatory power for low volatility ETFs. FF5 model shows that low volatility ETFs have significant positive exposure to market, profitability and investment factors and negative exposure to value, which is not found with the FFC model. The alpha of low volatility ETFs remains still significantly positive at 4.14% annually. In a final attempt to explain the performance of low volatility ETFs I add the volatility factor VOL to the Fama-French-Carhart model. The adjusted R^2 improves slightly to 0.737 but, importantly, the exposure to VOL is statistically significant (coefficient 0.361, t-statistic 6.231). Also, low volatility ETFs' alpha is reduced to 1.66% and is no longer statistically significant (t-statistic 0.917).

Table A5 in Appendix C reports the results for equally-weighted portfolios, which are similar to the value-weighted results discussed here. Most notable differences are the more significant positive exposure for SMB for all categories except large cap in the FF5 regression, and the better explanatory power for low volatility ETFs' performance with both models. However, these differences do not change the main results. To conclude, long-only portfolios in the FFC model do not significantly improve the regression estimates nor reveal any new factor exposures. Fama-French five-factor model shows that profitability and investment factors affect the performance of large cap, value, growth, and low volatility ETFs, but the intended factor exposures remain. All models fail to fully explains low volatility ETFs' performance but adding a proxy for the volatility factor makes their alpha insignificant.

4.3 Limitations of the study and suggestions for further research

The biggest concerns of my results relate to factor ETF classification, the in-category variation, and the lack of return history. I categorized the ETFs based on information provided on their factsheets and websites, but some ETFs are difficult to assign to just one category. For example, multifactor ETFs that provide exposure to several factors are increasingly popular nowadays but have been excluded from my analysis. There is also no guarantee that the ETFs follow the said investment strategies and the same strategies can be applied in multiple ways which adds to the in-category variation. ETFs as investment vehicles also exhibit their own risk characteristics such as tracking error and liquidity risk which can affect their performance. Despite these concerns I feel that the value- and equally-weighted portfolios of factor ETFs give reliable estimates of factors in real-life portfolios and can be used to evaluate real-life factor investing strategies. A bigger concern, one that limits all research on factor investing, is the lack of return history. Most factor ETFs have less than ten years of return data available and, for example, first low volatility ETFs were introduced in 2011. This means that we do not yet have return data of these factors in bad times, which might make their performance and significant alphas misleading. However, with ever increasing number of factor strategies implemented in real-life portfolios, and even more factors proposed in academic research, it is important to evaluate their performance and risk exposures also in practice.

5. Conclusion

In this thesis, I study the performance and risk exposure of U.S. factor ETFs and contribute to research on factor investing. I focus on ETFs following size (small and large cap), value (value and growth), momentum and low volatility strategies which are among the most common in the factor ETF market. Beginning with factor ETFs' performance, I first compare their returns and risk-adjusted performance to the academic long-only and long-short factor portfolios'. I find that factor ETFs' performance follows that of long-only rather than long-short factor portfolios and only small cap, value and low volatility ETFs deviate significantly from standard market ETFs. Surprisingly, most ETF categories beat their respective long-short counterparts on a risk-adjusted basis which gives support for the long-only approach to factor investing. However, the long-short factor portfolios' biggest benefit is their insignificant market exposure which promotes diversification benefits. The same cannot be said of the factor ETFs, though, as they all have significant market exposure and high co-movement with each other. Factor ETFs' return correlations are still less significant than those implied by the long-only factor portfolios.

After the performance evaluation I analyze the risk exposure of factor ETFs with several asset pricing models. From CAPM and Fama-French-Carhart (FFC) regression analyses I find that factor ETFs offer the intended risk exposures rather consistently but the market exposure remains significant. Only low volatility ETFs seem exceptional as their performance cannot fully be explained by exposure to market, size, value, and momentum factors. As a robustness test, I run the FFC regression with long-only factor portfolios and also test the Fama-French five-factor model. I find that the long-only FFC model does not significantly improve the regression estimates nor reveal any new factor exposures. The Fama-French five-factor model shows that profitability and investment factors affect the performance of large cap, value, growth, and low volatility ETFs but the intended factor exposures remain. All factor models fail to fully explain low volatility ETFs' performance and they are the only factor ETF category with statistically significant alphas. Overall, my results show that factor ETFs offer exposure to the intended factors, but due to the high market exposure, their performance is greatly driven by the market factor. Despite these concerns I argue that factor investing with factor ETFs can be beneficial in practice.

Appendix

Appendix A: Categorization of U.S. factor ETFs

Table A1 U.S. equity ETFs classified in factor ETF categories.
This table list all U.S. Equity ETFs used in this study and under which ETF categories there are classified. It also shows the ticker symbol, inception year, and net assets ($ Million) and annual expense ratios from June 2018 for all ETFs.

ETF Name	Ticker	Inception year	Net assets ($ Million)	Expense Ratio (ann.)
Size Small cap ETFs				
iShares Russell 2000 ETF	IWM	2000	47,059.3	0.20 %
iShares Core S&P Small-Cap ETF	IJR	2000	42,911.0	0.07 %
Vanguard Small-Cap ETF	VB	2004	23,646.6	0.05 %
iShares Morningstar Small-Cap ETF	JKJ	2004	250.3	0.25 %
iShares Micro-Cap ETF	IWC	2005	1,045.6	0.60 %
SPDR® S&P 600 Small Cap ETF	SLY	2005	1,044.7	0.15 %
Invesco Zacks Micro Cap ETF	PZI	2005	25.4	1.58 %
Invesco Wilshire Micro-Cap ETF	WMCR	2006	33.9	0.58 %
Schwab US Small-Cap ETF™	SCHA	2009	7,919.8	0.09 %
Vanguard Russell 2000 ETF	VTWO	2010	1,535.3	0.15 %
Vanguard S&P Small-Cap 600 ETF	VIOO	2010	940.8	0.15 %
SPDR® Portfolio Small Cap ETF	SPSM	2013	1,186.3	0.05 %
iShares Edge MSCI USA Size Factor ETF	SIZE	2013	202.3	0.15 %
NuShares ESG Small-Cap ETF	NUSC	2016	59.8	0.40 %
AdvisorShares Cornerstone Small Cap ETF	SCAP	2016	5.2	0.90 %
iShares Russell 2500 ETF	SMMD	2017	11.5	0.23 %
Oppenheimer Russell 1000 Size Factor ETF	OSIZ	2017	5.4	0.19 %
Invesco PureBeta MSCI USA Sm Cp	PBSM	2017	3.0	0.06 %
Value ETFs				
iShares Russell 1000 Value ETF	IWD	2000	36,104.5	0.20 %
iShares S&P 500 Value ETF	IVE	2000	14,625.3	0.18 %
iShares Russell 2000 Value ETF	IWN	2000	10,481.0	0.24 %
iShares S&P Small-Cap 600 Value ETF	IJS	2000	6,024.7	0.25 %
iShares S&P Mid-Cap 400 Value ETF	IJJ	2000	5,914.1	0.25 %
iShares Core S&P US Value ETF	IUSV	2000	3,897.2	0.05 %
SPDR® S&P 600 Small Cap Value ETF	SLYV	2000	1,502.9	0.15 %
SPDR® Portfolio S&P 500 Value ETF	SPYV	2000	1,349.7	0.04 %
iShares Russell Mid-Cap Value ETF	IWS	2001	10,835.6	0.25 %
Vanguard Value ETF	VTV	2004	38,728.1	0.05 %
Vanguard Small-Cap Value ETF	VBR	2004	13,475.9	0.07 %
iShares Morningstar Small-Cap Value ETF	JKL	2004	442.2	0.30 %
iShares Morningstar Mid-Cap Value ETF	JKI	2004	429.8	0.30 %
iShares Morningstar Large-Cap Value ETF	JKF	2004	381.2	0.25 %
Invesco Dynamic Large Cap Value ETF	PWV	2005	1,312.3	0.56 %
SPDR® S&P 400 Mid Cap Value ETF	MDYV	2005	767.4	0.15 %
Invesco Russell 2000 Pure Value ETF	PXSV	2005	75.5	0.39 %
Invesco Russell Midcap Pure Val ETF	PXMV	2005	46.6	0.39 %
Vanguard Mid-Cap Value ETF	VOE	2006	8,752.0	0.07 %
Invesco S&P 500® Pure Value ETF	RPV	2006	890.8	0.35 %
Invesco S&P SmCp 600® Pure Val ETF	RZV	2006	177.9	0.35 %
Invesco S&P MidCap 400® PureVal ETF	RFV	2006	112.7	0.35 %
Vanguard Mega Cap Value ETF	MGV	2007	1,946.2	0.07 %
First Trust Large Cap Val AlphaDEX® ETF	FTA	2007	1,049.0	0.62 %
First Trust Multi Cap Val AlphaDEX® ETF	FAB	2007	89.9	0.66 %
Schwab US Large-Cap Value ETF™	SCHV	2009	4,297.4	0.05 %
iShares Russell Top 200 Value ETF	IWX	2009	297.7	0.20 %
Vanguard Russell 1000 Value ETF	VONV	2010	1,374.0	0.12 %
Vanguard S&P 500 Value ETF	VOOV	2010	817.7	0.15 %
Vanguard S&P Mid-Cap 400 Value ETF	IVOV	2010	692.6	0.20 %
Vanguard S&P Small-Cap 600 Value ETF	VIOV	2010	366.5	0.20 %
Vanguard Russell 2000 Value ETF	VTWV	2010	202.8	0.20 %
Invesco Russell Top 200 Pure Val ETF	PXLV	2011	103.7	0.39 %
First Trust Small Cap Val AlphaDEX® ETF	FYT	2011	67.4	0.70 %
First Trust Mid Cap Value AlphaDEX® ETF	FNK	2011	48.6	0.70 %
SPDR® S&P 1500 Value Tilt ETF	VLU	2012	15.3	0.12 %
iShares Edge MSCI USA Value Factor ETF	VLUE	2013	3,527.4	0.15 %
Deep Value ETF	DVP	2014	143.0	0.58 %
SPDR® MFS Systematic Value Equity ETF	SYV	2014	33.2	0.60 %
Invesco S&P 500 Enhanced Value	SPVU	2015	25.4	0.13 %
Fidelity® Value Factor ETF	FVAL	2016	82.3	0.29 %
NuShares ESG Mid-Cap Value ETF	NUMV	2016	43.8	0.40 %
NuShares ESG Large-Cap Value ETF	NULV	2016	38.5	0.35 %
JPMorgan US Value Factor ETF	JVAL	2017	26.8	0.52 %
Oppenheimer Russell 1000 Value Fac ETF	OVLU	2017	5.2	0.19 %
Principal Contrarian Value ETF	PVAL	2017	3.9	0.29 %
Vanguard US Value Factor ETF	VFVA	2018	33.4	0.13 %

ETF Name	Ticker	Inception year	Net assets ($ Million)	Expense Ratio (ann.)
Size Large cap ETFs				
SPDR® S&P 500 ETF	SPY	1993	259,311.7	0.01 %
Invesco QQQ ETF	QQQ	1999	65,990.8	0.20 %
iShares Core S&P 500 ETF	IVV	2000	148,293.4	0.04 %
iShares Russell 1000 ETF	IWB	2000	20,312.1	0.15 %
iShares S&P 100 ETF	OEF	2000	4,664.4	0.20 %
Vanguard Large-Cap ETF	VV	2004	12,774.4	0.05 %
iShares Morningstar Large-Cap ETF	JKD	2004	938.7	0.20 %
SPDR® Portfolio Large Cap ETF	SPLG	2005	1,345.3	0.03 %
Vanguard Mega Cap ETF	MGC	2007	1,438.2	0.07 %
Schwab US Large-Cap ETF™	SCHX	2009	12,660.1	0.03 %
iShares Russell Top 200 ETF	IWL	2009	148.1	0.15 %
Vanguard S&P 500 ETF	VOO	2010	90,979.3	0.04 %
Vanguard Russell 1000 ETF	VONE	2010	902.3	0.12 %
Schwab 1000 Index ETF	SCHK	2017	409.7	0.05 %
Growth ETFs				
iShares S&P Mid-Cap 400 Growth ETF	IJK	2000	8,215.7	0.25 %
iShares S&P Small-Cap 600 Growth ETF	IJT	2000	6,197.9	0.25 %
iShares Core S&P US Growth ETF	IUSG	2000	4,530.2	0.05 %
iShares S&P 500 Growth ETF	IVW	2000	20,993.0	0.18 %
iShares Russell 1000 Growth ETF	IWF	2000	42,277.2	0.20 %
iShares Russell 2000 Growth ETF	IWO	2000	10,972.5	0.24 %
SPDR® S&P 600 Small Cap Growth ETF	SLYG	2000	1,990.8	0.15 %
SPDR® Portfolio S&P 500 Growth ETF	SPYG	2000	2,640.0	0.04 %
iShares Russell Mid-Cap Growth ETF	IWP	2001	8,902.8	0.25 %
iShares Morningstar Large-Cap Growth ETF	JKE	2004	978.2	0.25 %
iShares Morningstar Mid-Cap Growth ETF	JKH	2004	273.6	0.30 %
iShares Morningstar Small-Cap Growth ETF	JKK	2004	198.5	0.30 %
Vanguard Small-Cap Growth ETF	VBK	2004	8,335.6	0.07 %
Vanguard Growth ETF	VUG	2004	35,363.8	0.05 %
SPDR® S&P 400 Mid Cap Growth ETF	MDYG	2005	1,212.5	0.15 %
Invesco Dynamic Large Cap Growth ETF	PWB	2005	614.0	0.57 %
Invesco Russell Midcap Pure Gr ETF	PXMG	2005	222.7	0.39 %
Invesco Russell 2000 Pure Growth ETF	PXSG	2005	71.3	0.39 %
Invesco S&P MidCap 400® Pure Gr ETF	RFG	2006	614.4	0.35 %
Invesco S&P 500® Pure Growth ETF	RPG	2006	2,458.1	0.35 %
Invesco S&P SmCp 600® Pure Gr ETF	RZG	2006	298.5	0.35 %
Vanguard Mid-Cap Growth ETF	VOT	2006	5,630.3	0.07 %
First Trust Multi Cap Gr AlphaDEX® ETF	FAD	2007	176.8	0.70 %
First Trust Large Cap Gr AlphaDEX® ETF	FTC	2007	874.1	0.62 %
Vanguard Mega Cap Growth ETF	MGK	2007	3,832.5	0.07 %
iShares Russell Top 200 Growth ETF	IWY	2009	1,069.1	0.20 %
Schwab US Large-Cap Growth ETF™	SCHG	2009	6,149.5	0.04 %
Vanguard S&P Mid-Cap 400 Growth ETF	IVOG	2010	828.7	0.20 %
Vanguard S&P Small-Cap 600 Growth ETF	VIOG	2010	422.1	0.20 %
Vanguard Russell 1000 Growth ETF	VONG	2010	1,852.7	0.12 %
Vanguard S&P 500 Growth ETF	VOOG	2010	2,111.9	0.15 %
Vanguard Russell 2000 Growth ETF	VTWG	2010	296.5	0.20 %
First Trust Mid Cap Growth AlphaDEX® ETF	FNY	2011	186.3	0.70 %
First Trust Small Cap Gr AlphaDEX® ETF	FYC	2011	308.1	0.70 %
Invesco Russell Top 200 Pure Gr ETF	PXLG	2011	231.3	0.39 %
SPDR® MFS Systematic Growth Equity ETF	SYG	2014	44.4	0.60 %
Janus Henderson Small Cap Gr Alpha ETF	JSML	2016	14.4	0.50 %
Janus Henderson Small/Md Cp Gr Alpha ETF	JSMD	2016	36.3	0.50 %
NuShares ESG Large-Cap Growth ETF	NULG	2016	49.7	0.35 %
NuShares ESG Mid-Cap Growth ETF	NUMG	2016	46.9	0.40 %
ClearBridge All Cap Growth ETF	CACG	2017	68.5	0.53 %
ClearBridge Large Cap Growth ESG ETF	LRGE	2017	4.7	0.59 %

(continued on next page)

Table A1 (continued)

Momentum ETFs				
Invesco DWA Momentum ETF	PDP	2007	1,704.5	0.63 %
Invesco DWA SmallCap Momentum ETF	DWAS	2012	399.8	0.60 %
SPDR® S&P 1500 Momentum Tilt ETF	MMTM	2012	29.9	0.12 %
iShares Edge MSCI USA Momentum Fctr ETF	MTUM	2013	9,319.0	0.15 %
Invesco DWA NASDAQ Momentum ETF	DWAQ	2014	66.6	0.85 %
SPDR® Russell 1000 Momentum ETF	ONEO	2015	602.1	0.20 %
Alpha Architect US Quantitative Momt ETF	QMOM	2015	47.6	0.79 %
Invesco S&P 500 Momentum	SPMO	2015	37.1	0.13 %
Fidelity® Momentum Factor ETF	FDMO	2016	95.3	0.29 %
Aptus Behavioral Momentum ETF	BEMO	2017	47.5	0.79 %
JPMorgan US Momentum Factor ETF	JMOM	2017	28.2	0.52 %
ALPS/Dorsey Wright Sector Momentum ETF	SWIN	2017	10.9	0.40 %
Principal Sustainable Momentum ETF	PMOM	2017	5.6	0.29 %
Oppenheimer Russell 1000 Momt Fac ETF	OMOM	2017	5.4	0.19 %
Vanguard US Momentum Factor ETF	VFMO	2018	20.3	0.13 %

Market ETFs				
Vanguard Total Stock Market ETF	VTI	2000	97,389.5	0.04 %
iShares Russell 3000 ETF	IWV	2000	9,331.7	0.20 %
SPDR® Portfolio Total Stock Market ETF	SPTM	2000	2,190.7	0.03 %
iShares Core S&P Total US Stock Mkt ETF	ITOT	2004	14,510.9	0.03 %
Schwab US Broad Market ETF™	SCHB	2009	12,257.6	0.03 %
Vanguard Russell 3000 ETF	VTHR	2010	386.7	0.15 %
Invesco PureBeta MSCI USA	PBUS	2017	2.7	0.04 %

Low volatility ETFs				
iShares Edge MSCI Min Vol USA ETF	USMV	2011	14,745.9	0.15 %
Invesco S&P 500 Low Volatility ETF	SPLV	2011	7,035.6	0.25 %
Invesco S&P MidCap Low Volatil ETF	XMLV	2013	1,344.5	0.25 %
Invesco S&P SmallCap Low Volatil ETF	XSLV	2013	1,287.7	0.25 %
SPDR® SSGA US Small Cap Low Volatil ETF	SMLV	2013	204.8	0.12 %
SPDR® SSGA US Large Cap Low Volatil ETF	LGLV	2013	103.7	0.12 %
VictoryShares US 500 Volatility Wtd ETF	CFA	2014	568.3	0.35 %
Legg Mason Low Volatility High Div ETF	LVHD	2015	591.5	0.27 %
JPMorgan Diversified Return US Eq ETF	JPUS	2015	540.0	0.47 %
SPDR® Russell 1000 Low Vol Foc ETF	ONEV	2015	456.9	0.20 %
Invesco S&P 500ex-Rate SnsvLwVtl ETF	XRLV	2015	177.6	0.25 %
VictoryShares US LgCp Hi Div Vol Wtd ETF	CDL	2015	145.0	0.35 %
VictoryShares US SmCp Hi Div Vol Wtd ETF	CSB	2015	43.7	0.35 %
VictoryShares US Small Cap Vol Wtd ETF	CSA	2015	41.5	0.35 %
First Trust Hrzn MgdVolatil Domestic ETF	HUSV	2016	119.4	0.70 %
Fidelity® Low Volatility Factor ETF	FDLO	2016	59.0	0.29 %
iShares Edge MSCI Min Vol USA Sm-Cp ETF	SMMV	2016	34.3	0.20 %
Franklin Liberty US Low Volatility ETF	FLLV	2016	12.3	0.50 %
Invesco US Lg Cp Optimized Vol ETF	OVLC	2016	1.5	0.30 %
Principal US Mega-Cap Multi-Factor ETF	USMC	2017	1,680.0	0.12 %
Nationwide Risk-Based US Equity ETF	RBUS	2017	116.7	0.30 %
QuantX Dynamic Beta US Equity ETF	XUSA	2017	44.5	0.29 %
JPMorgan US Minimum Volatility ETF	JMIN	2017	27.0	0.52 %
Hartford Multifactor LowVolatil US EqETF	LVUS	2017	5.4	0.22 %
Oppenheimer Russell 1000 Low Vol Fac ETF	OVOL	2017	5.1	0.19 %
Invesco S&P 500 Minimum Variance	SPMV	2017	1.4	0.10 %
Vanguard US Minimum Volatility ETF	VFMV	2018	12.2	0.13 %

Appendix B: Construction of low volatility and long-only factor portfolios

Low volatility factor VOL is constructed from time-series of volatility sorted portfolios provided by Petri Jylhä. Each month all CRSP stocks are sorted into deciles based on the trailing three-year monthly volatility, and the value-weighted returns of the portfolios are calculated. This method is similar to Baker et al. (2011) who studies the performance of volatility quintile portfolios sorted on their five-year trailing volatility. The long-short factor portfolio is constructed similarly to Fama-French SMB-factor (Fama & French, 1993) by taking the average of the three deciles (top 30 %) with the lowest volatility and subtracting the average return of the three deciles with highest volatility. The long-only low volatility factor is the average of the three decile portfolios with the lowest volatility. Data for the volatility factor is available from 01/1963 to 3/2018.

To construct the long-only risk factor portfolios for size, value and momentum, I applied the methodology of Fama-French research factors (Fama & French, 1993; 2015) and Carhart's (1997) momentum factor. This method has been used by e.g. Tuokko (2017) in his study of factor indices and their usefulness for factor investing. Fama-French research factors SMB and HML, and Carhart's (1997) momentum factor WML are constructed from 2×3 sorts on size and book-to-market, or momentum. The 2×3 sorts are value-weighted portfolios of stocks with similar characteristics: small capitalization value, neutral, and growth stocks, and large capitalization value, neutral, and growth stocks, for example. Kenneth French's data library [12] offers the return data of these sub-portfolios under the title 6 Portfolios Formed on Size and Book-to-Market (2×3) and 6 Portfolios Formed on Size and Momentum (2×3).

[12] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

The long-only risk factors are constructed using only the returns of long (short) -side portfolios, otherwise following the same methodology as Fama-French (1993, 2015). The exact calculations to form size long-only (small and large cap), value long-only (value and growth), and momentum long-only (winners) time-series are shown in equations $(5) - (9)$.

$$Small\ Cap_t = (Small\ Value_t + Small\ Neutral_t + Small\ Growth_t)/3 \quad (5)$$

$$Large\ Cap_t = (Large\ Value_t + Large\ Neutral_t + Large\ Growth_t)/3 \quad (6)$$

$$Value_t = (Small\ Value_t + Large\ Value_t)/2 \quad (7)$$

$$Growth_t = (Small\ Growth_t + Large\ Growth_t)/2 \quad (8)$$

$$Winners_t = (Small\ Up_t + Large\ Up_t)/2 \quad (9)$$

'Up' refers to stocks with high return momentum in the past $t - 12$ to $t - 2$ months (winners). All sub-portfolio returns are value-weighted and long-only portfolio returns are equally-weighted.

Appendix C: Results for equally-weighted factor ETF portfolios

Table A2 Performance of U.S. factor ETFs (equally-weighted portfolios).
This table reports performance measures of equally-weighted portfolios of U.S. factor ETFs. Sample period ends in June 2018 for all categories.

Annualized	**Small cap**	**Large cap**	**Value**	**Growth**	**Momentum**	**Low volatility**	**Market**
Average return	8.68 %	6.09 %	8.80 %	6.09 %	8.45 %	13.12 %	6.01 %
Standard deviation	18.61 %	14.29 %	16.02 %	17.37 %	16.98 %	8.72 %	14.53 %
Sharpe ratio	0.38	0.32	0.45	0.26	0.46	1.47	0.31
CAPM alpha	2.02 %	-0.06 %	2.56 %	-0.58 %	-0.24 %	4.68 %	-0.20 %
(t-statistic)	(1.115)	(-0.147)	(1.723)	(-0.576)	(-0.126)	(2.328)	(-0.570)
CAPM beta	1.15	0.96	0.99	1.14	1.05	0.63	0.97
Sample starts	June 2000	June 2000	June 2000	June 2000	April 2007	June 2011	June 2000

Table A3 Correlations of U.S. factor ETFs (equally-weighted portfolios).
This table reports the correlations of monthly returns of value-weighted factor ETF portfolios.

ETF category		**Market**	**Small-cap**	**Large-cap**	**Value**	**Growth**	**Momentum**	**Low volatility**
Market		1.00						
Size	Small cap	0.91	1.00					
	Large cap	0.99	0.88	1.00				
Value	Value	0.94	0.94	0.91	1.00			
	Growth	0.96	0.92	0.95	0.87	1.00		
Momentum		0.92	0.89	0.92	0.86	0.96	1.00	
Low volatility		0.84	0.78	0.82	0.82	0.80	0.78	1.00

Table A4 Results from CAMP and Fama-French-Carhart regressions (equally-weighted portfolios).
This table shows the regression results from CAPM and Fama-French-Carhart regressions using monthly equally-weighted returns of ETF portfolios starting from the launch of the first ETF in each category. Alphas of both models are annualized and the t-statistics are presented below the coefficients in italics. Sample ends in June 2018 for all ETF categories.

ETF category	**Obs.**	**CAPM**			**Fama-French-Carhart Model**					
		Alpha	Mkt-Rf	R^2	Alpha	Mkt-Rf	SMB	HML	WML	Adj. R^2
Market	217	**-0.20 %**	**0.975**	0.990	**-0.15 %**	**0.978**	**-0.047**	**0.063**	**-0.014**	0.993
		-0.570	*144.849*		*-0.490*	*149.626*	*-4.801*	*7.679*	*-2.715*	
Size Small cap	217	**2.02 %**	**1.145**	0.836	**-1.50 %**	**1.024**	**0.754**	**0.164**	**0.019**	0.980
		1.115	*33.056*		*-2.370*	*73.644*	*36.402*	*9.380*	*1.703*	
Large cap	217	**-0.06 %**	**0.958**	0.986	**0.48 %**	**0.973**	**-0.130**	**0.014**	**-0.016**	0.992
		-0.147	*122.123*		*1.592*	*148.314*	*-13.306*	*1.723*	*-3.063*	
Value Value	217	**2.56 %**	**0.995**	0.852	**0.56 %**	**0.939**	**0.226**	**0.446**	**-0.060**	0.968
		1.723	*35.137*		*0.805*	*62.339*	*10.091*	*23.482*	*-5.002*	
Growth	217	**-0.58 %**	**1.136**	0.940	**-0.78 %**	**1.085**	**0.254**	**-0.249**	**0.006**	0.973
		-0.576	*58.082*		*-1.143*	*72.894*	*11.455*	*-13.249*	*0.483*	
Momentum	135	**-0.24 %**	**1.053**	0.865	**-1.82 %**	**1.116**	**0.226**	**-0.207**	**0.172**	0.913
		-0.126	*29.153*		*-1.200*	*34.172*	*3.970*	*-3.841*	*5.763*	
Low volatility	85	**4.68 %**	**0.633**	0.677	**4.09 %**	**0.645**	**0.069**	**0.056**	**0.128**	0.684
		2.328	*13.203*		*2.039*	*12.705*	*0.965*	*0.680*	*2.227*	

Table A5 Additional regressions with long-only FFC and Fama-French five-factor models (EW portfolios).
This table shows the regression results from Fama-French-Carhart model with long-only factors and Fama-French five-factor model. Alphas of both models are annualized and the t-statistics are presented below the coefficients in italics. Sample periods and number of observations are the same as in CAPM and FFC regressions in Table 6.

ETF category	**Fama-French-Carhart Model Long-Only**						**Fama-French Five Factor Model**						
	Alpha	Mkt-Rf	Small-Cap	Value	Winners	Adj. R^2	Alpha	Mkt-Rf	SMB	HML	RMW	CMA	Adj. R^2
Market	**-0.13 %**	**0.986**	**-0.071**	**0.102**	**-0.040**	0.993	**-0.66 %**	**1.004**	**-0.035**	**0.049**	**0.059**	**0.002**	0.993
	-0.426	*64.185*	*-4.190*	*7.322*	*-2.781*		*-2.175*	*140.804*	*-3.532*	*4.510*	*4.659*	*0.107*	
Size Small cap	**-1.34 %**	**0.108**	**0.719**	**0.080**	**0.107**	0.981	**-1.86 %**	**1.035**	**0.769**	**0.137**	**0.060**	**0.017**	0.980
	-2.179	*3.437*	*20.727*	*2.808*	*3.635*		*-2.813*	*66.387*	*35.577*	*5.801*	*2.154*	*0.497*	
Large cap	**0.46 %**	**1.110**	**-0.128**	**0.045**	**-0.053**	0.992	**-0.01 %**	**0.998**	**-0.121**	**-0.001**	**0.051**	**0.009**	0.993
	1.486	*71.449*	*-7.489*	*3.224*	*-3.598*		*-0.021*	*137.010*	*-11.944*	*-0.075*	*3.903*	*0.591*	
Value Value	**0.82 %**	**0.411**	**0.040**	**0.595**	**-0.118**	0.961	**-1.22 %**	**1.029**	**0.250**	**0.362**	**0.155**	**0.123**	0.970
	1.075	*10.586*	*0.939*	*16.934*	*-3.233*		*-1.746*	*62.822*	*11.030*	*14.589*	*5.329*	*3.458*	
Growth	**-1.06 %**	**1.028**	**0.443**	**-0.416**	**0.047**	0.971	**-0.40 %**	**1.069**	**0.260**	**-0.188**	**0.002**	**-0.147**	0.975
	-1.506	*28.699*	*11.230*	*-12.808*	*1.395*		*-0.580*	*66.354*	*11.656*	*-7.716*	*0.058*	*-4.208*	
Momentum	**-1.13 %**	**0.604**	**0.011**	**-0.223**	**0.669**	0.922	**-1.32 %**	**1.062**	**0.217**	**-0.300**	**-0.028**	**-0.067**	0.891
	-0.783	*5.988*	*0.109*	*-2.645*	*7.454*		*-0.746*	*27.545*	*3.280*	*-4.403*	*-0.276*	*-0.566*	
Low volatility	**4.90 %**	**0.669**	**0.186**	**-0.142**	**-0.089**	0.667	**3.91 %**	**0.677**	**0.163**	**-0.210**	**0.311**	**0.479**	0.746
	2.396	*4.084*	*1.153*	*-0.974*	*-0.538*		*2.175*	*14.762*	*2.273*	*-2.456*	*2.886*	*3.696*	

Appendix D: Correlations of long-short and long-only factor portfolios

Table A6 Correlations of long-short and long-only factor portfolios.
This table shows the correlations of long-short and long-only risk factor portfolios. Panel A reports the correlations of long-short risk factors: Mkt-Rf (market, excess return), SMB (size), HML (value), WML (momentum), and VOL (low−high volatility). Panel B reports the correlations of long-only portfolios whose construction is presented in Appendix B. Sample periods follow that of factor ETFs in Table 5.

Panel A Long-short factor portfolios

Risk factor	Mkt-Rf	SMB	HML	WML	VOL
Mkt-Rf	1.00				
SMB	0.29	1.00			
HML	-0.04	0.12	1.00		
WML	-0.35	-0.23	-0.44	1.00	
VOL	-0.59	-0.67	-0.11	0.29	1.00

Panel B Long-only factor portfolios

Long-only factor		Market	Small cap	Large cap	Value	Growth	Winners	Low volatility
Market		1.00						
Size	Small cap	0.90	1.00					
	Large cap	0.97	0.88	1.00				
Value	Value	0.88	0.93	0.94	1.00			
	Growth	0.96	0.93	0.89	0.83	1.00		
Momentum	Winners	0.94	0.93	0.92	0.88	0.96	1.00	
Low volatility		0.97	0.81	0.96	0.83	0.89	0.88	1.00

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